Analyzing physiological data in order to accurately measure stress in virtual reality

Jothika Saravanarajan
Mentored by Dr. J. Cortney Bradford and Dr. W. David Hairston

Introduction

Stress is induced by different physical and psychological pressures of an environment. These pressures affect responses of the body (Cho et al., 2017) which is described as physiological stress. Stress is studied because it affects the ability to maintain homeostasis and it is universal to everyone. During a virtual reality (VR) simulation, stress is broadened to include VR sickness and anxiety from being in an unfamiliar environment.

Electrocardiograms (ECG) measure electrical activity from the heart, which reflect changes in the autonomic nervous system (ANS). Changes in the ANS are linked to arousal, anxiety, stress, and fatigue. Increased heart rate (HR) is a sign of stress, however, an increase in heart rate variability (HRV), a feature of an ECG signal, means a person is less stressed (Neubauer et al., 2020). Acceleration is also a valuable metric to measure because there is evidence which suggests gait is reflective of emotional states (Zhang et al., 2016). An increase in acceleration (increased movement) suggests a user is more stressed.

HR, HRV, and acceleration are non-intrusive and user-friendly methods of stress quantification. This project aimed to determine which metric was best suited for quantifying physiological stress in virtual reality.

Materials and Methods

Fifteen volunteers were tested at Aberdeen Proving Ground. The Tobii HTC Vive Pro Eye head-mounted display (Figure 1) was attached to the Wearable Sensing DSI-VR300, an electroencephalogram device. Two Zephyr BioHarnesses were used. One was attached to the chest to collect ECG and acceleration, while the other was attached to the dominant calf, with Velcro, to collect leg acceleration data. All data streams were collected via Lab Streaming Layer (LSL) on a laptop.

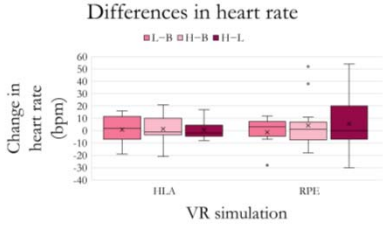
Figure 1: A student was testing in VR with the plank to increase immersion. The leg BioHarness was attached to the dominant (right) leg with a 3D-printed case and a Velcro strap.

Materials and Methods (continued)

Another laptop was utilized to run the VR simulations, a custom paradigm of Half-Life: Alyx (HLA) and Richie's Plank Experience (RPE). HLA and RPE are simulations that place the participant on planks at a high altitude. There were three stress levels, baseline (B), low (L), and high (H), for each simulation. All simulations except RPE high-stress lasted for 90 seconds. RPE high-stress lasted 150 seconds. Two-minute breaks were given between simulations to return to homeostasis. A wood plank was taped to the floor for increased immersion.

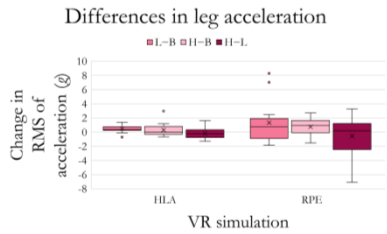
Results

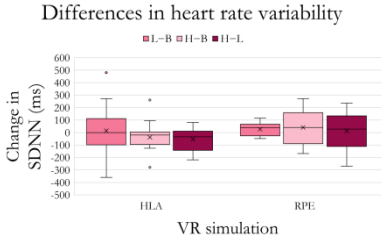
The initial sample size was $n = 15$, but two participants were omitted due to data transmission errors. The data was extracted and processed from the XDF file format exported by LSL with a MATLAB script. HRVTool, a MATLAB application, was used to calculate global HR and standard deviation of normal heart beats (SDNN), a metric of HRV, from the clean ECG signal. First, the accelerometry data was filtered with a high-pass filter to reduce noisiness, then root mean square (RMS) was calculated from the resultant accelerations of the leg and chest for the global time domain.



Graph 1 (left): A non-parametric Friedman test (FT) showed there was no significant difference between baseline HLA (*Mdn* = 61), low HLA (*Mdn* = 63), and high HLA (*Mdn* = 61) for the heart rate, $\chi^2(2) = 1.19$, $p = .551$. There was no significant difference between baseline RPE (*Mdn* = 59), low RPE (*Mdn* = 61), and high RPE (*Mdn* = 61), $\chi^2(2) = 0.81$, $p = .668$.

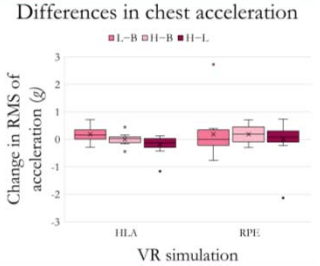
Graph 2 (right): Another FT showed there was no significant difference between baseline HLA (*Mdn* = 411.7), low HLA (*Mdn* = 416.4), and high HLA (*Mdn* = 387.0) for the SDNN of the ECG signal, $\chi^2(2) = 1.88$, $p = .390$. There was also no significant difference between baseline RPE (*Mdn* = 353.0), low RPE (*Mdn* = 383.2), and high RPE (*Mdn* = 402.5), $\chi^2(2) = 2.00$, $p = .368$.





Graph 3 (left): A FT showed there was no significant difference between baseline HLA (*Mdn* = 1.85), low HLA (*Mdn* = 2.19), and high HLA (*Mdn* = 1.89) for the resultant acceleration of the dominant leg, $\chi^2(2) = 5.69$, $p = .058$. There was no significant difference between baseline RPE (*Mdn* = 2.13), low RPE (*Mdn* = 2.89), and high RPE (*Mdn* = 3.07), $\chi^2(2) = 3.85$, $p = .146$.

Results (continued)



Graph 4 (left): A FT showed there was no significant difference between baseline HLA (*Mdn* = 1.08), low HLA (*Mdn* = 1.24), and high HLA (*Mdn* = 1.11) for the resultant acceleration of the chest, $\chi^2(2) = 4.31$, $p = .116$. There was also no significant difference between baseline RPE (*Mdn* = 1.26), low RPE (*Mdn* = 1.29), and high RPE (*Mdn* = 1.41), $\chi^2(2) = 2.92$, $p = .232$.

Conclusions

The purpose of this project was to determine the best metric for quantitative stress analysis in VR, which was partially met. Of the eight Friedman tests run (Graphs 1–4), none were significant. However, leg acceleration in the HLA simulation trended towards significance with a p-value of .058.

Some limitations of the study included the data quality and task validity. Since the participants took part in dynamic tasks, the data remained noisy after filtration, which affected the script analysis for all signals. The task also varied between HLA and RPE, which could be considered a confounding variable.

Currently, medical professionals do not have standardized quantitative stress testing in clinical settings. By utilizing these metrics, they could obtain an unbiased measure of an individual's stress level to treat phobias, post-traumatic stress disorder, etc. Further research should include analyzing other metrics within the ECG and accelerometer signals to determine if other metrics are viable for objective stress analysis.

References

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